Hybrid response surface methodology–artificial neural network optimization of drying process of banana slices in a forced convective dryer

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Abstract
The aim of the study is to fit models for predicting surfaces using the response surface methodology and the artificial neural network to optimize for obtaining the maximum acceptability using desirability functions methodology in a hot air drying process of banana slices. The drying air temperature, air velocity, and drying time were chosen as independent factors and moisture content, drying rate, energy efficiency, and exergy efficiency were dependent variables or responses in the mentioned drying process. A rotatable central composite design as an adequate method was used to develop models for the responses in the response surface methodology. Moreover, isoresponse contour plots were useful to predict the results by performing only a limited set of experiments. The optimum operating conditions obtained from the artificial neural network models were moisture content 0.14 g/g, drying rate 1.03 g water/g h, energy efficiency 0.61, and exergy efficiency 0.91, when the air temperature, air velocity, and drying time values were equal to −0.42 (74.2 °C), 1.00 (1.50 m/s), and −0.17 (2.50 h) in the coded units, respectively.

Keywords
Artificial neural networks, response surface methodology, optimization, energy, exergy, drying

INTRODUCTION
Banana is rich in vitamin B6 and there are lots of ingredients such as fiber, vitamin C, magnesium, and potassium in banana content. Banana contains rich glue, fructose, and a variety of enzymes which lead not only to storage difficulties, but flesh browning during the processing (Chen et al., 2016). Drying is an essential operation in the chemical, agricultural, biotechnology, food, polymer, ceramics, pharmaceutical, pulp and paper, mineral processing, and wood processing industries. Concurrent heat and mass transfer operations are performed to remove the moisture content, which results in the transfer of moisture within the material to its surface and then water removal from the material to the atmosphere (Mujumdar, 2014; Onwude et al., 2016). The reduction of moisture is one of the oldest techniques in food preservation. Mechanical and thermal methods are two basic methods to remove the moisture in a solid material (Karimi et al., 2012; Lechtsanska et al., 2015; Tavakolipour and Mokhtarian, 2016). In drying process, knowledge of heat and mass transport is the basis of engineering design and process optimization, energy savings, and...
product quality. Because of specific attention to efficient mass transfer analysis and reproducibility of quality-controlled products, assigning of mass transport parameters are important in drying models. During the drying process, continuously changing conditions make it difficult to define the time duration of the process, and the most appropriate values for the conditions to achieve an effective drying process (Corzo et al., 2008). The most popular method for drying of food and agricultural products is convective drying (Doymaz, 2008; Naderinezhad et al., 2016). Sun and oven drying, as primary method of processing, are frequently performed by raw material producers, often with simple techniques in bad phytosanitary conditions (Dudaš et al., 2013). Drying air temperature and velocity, relative humidity, and initial moisture content of the product are the effective features of air drying (Taheri-Garavand et al., 2011a; Zlatanovic et al., 2013).

Modeling and optimization is one of the vital stages in a thermal process to increase the efficiency of the process. Drying processes are complex and involved highly non-linear phenomena. Hence, it is difficult to quantify the complex relationships between inputs and outputs of a drying process based on analytical methods in finding constants and solving the complexities of non-linear behaviors. The relationship between interfering factors and final outputs is of great value for researchers and engineers (Nikbakht et al., 2014).

Response surface methodology (RSM) is an empirical statistical technique employed for multiple regression analysis by using quantitative data obtained from properly designed experiments to solve multivariate equations (Wang et al., 2014).

The main purpose of RSM is optimization of an unidentified and noisy function with simpler approximating functions that are valid over a small region using designed experiments. The process improvement is accomplished by moving the operating conditions of a process using a sequence of experimental designs (Karimi et al., 2012). Design, development, and improvement of the product can be done according to the usage of RSM in industry. It also can be applied for formulation of new products. It means that the controlling or independent variables influence alone and also in combination on the response in the processes. In general, RSM which includes factorial design and also regression analysis helps to evaluate the effective factors and to build the models in order to study the interactions and to select the optimum conditions of a desirable response. As well as, a mathematical model is developed by this experimental methodology, by analyzing the effects of the controlling variables, which describes the food and industrial process (Karacadobey et al., 2016; Nakhhostin Panahi et al., 2013). Despite the RSM has so many advantages, it would be unwarranted to say that RSM is applicable to optimize and fit for all modeling studies.

Artificial neural networks (ANNs) are intelligent modeling systems based on the relationship between dependent (output) and independent (input) variables. They are composed of simple elements operating in parallel (Taheri-Garavand et al., 2015). These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. It is learnt from repetitive examples and doesn’t need any previous knowledge about relations between variables under study. Each example contains both inputs (information used to make a decision) and patterns (prediction or responses). The ANN tries each example in turn using the inputs to calculate responses which are compared with the pattern provided (outputs). The ANN corrects the network by making changes to internal connections (weights), when there is error. The trial and error process continues until the network outputs reach good adaptation with patterns to a certain stated level of accuracy.

ANNs can be used when there is no exact mathematical information. Additional benefit of an ANN model compared to a rule based model is that, if the process under analysis changes, new data can be added and the network can be trained again. ANN’s disadvantage compared with the RSM is the difficulty in describing the relationship between independent (inputs) and dependent (outputs) variables because of using vaguely defined weights, which is a black box. Response surface plotted by three dimensional plan can provide a good way of visualizing the parameter interactions for analyzing of designed process in comparison with ANNs (Karimi et al., 2012).

Most real life procedures must be optimized according to the numerous criteria at the same time. Commonly, operating conditions need to satisfy several conditions or constraints on responses. In a process design, it is necessary to satisfy the product characteristics to control the performance while using it.

In recent studies, the influence of air drying conditions on changes in moisture content, drying rate (DR), energy efficiency, and exergy efficiency of banana drying process has not been studied; hence, to optimize the drying process, the current research focused on modeling the influence of the air temperature, air velocity, and drying time (as independent variables) on changes in moisture content, DR, energy efficiency, and exergy efficiency (as dependent variables) of a hot air drying process for banana slices with thickness of 4 mm, by using RSM and ANN methods. The study, also, presented a specific point for the three independent variables in maximum desirability to obtain a minimum value for moisture content and a maximum value...
for DR, energy efficiency, and exergy efficiency to the extent possible based on the desirability functions by the designed ANN.

**MATERIALS AND METHODS**

Fresh bananas were daily purchased from a local market. The thin-layer drying experiments were conducted by forced conductive dryer which was designed and fabricated by Taheri-Garavand. Figure 1 shows a schematic diagram of the dryer. The heating structure consisted of 10 heating elements placed inside the dryer channel. Moreover, a simple control system was applied to control and adjust the temperature, relative humidity, and velocity of air used for drying process (Taheri-Garavand et al., 2011b). The instruments used for various measurements with their specifications are given in Table 1. The trays were supported by lightweight steel rods placed under the digital balance. The opening on the right of the tunnel was employed to load or unload the material. The dryer is capable of providing any desired drying air temperature in the range of 20–120°C, air relative humidity in the range of 5–95%, and air velocity in the range of 0.1–5.0 m/s with high accuracy. The dryer was adjusted to a preset air drying condition for about 20 min prior to achieve the steady state.

Then, the tray holding the samples was carefully kept in the dryer. The sample weight was kept constant at 65 g (±0.5 g) for all runs. During the course of the drying process, banana slices with thickness of 4 mm were weighed using a digital balance connected to a computer. The hot air drying was applied until the weight of samples reduced to a level corresponding to moisture content of about 0.2% d.b. The initial and final moisture contents of the banana slices were determined at 78°C initially and after 48 h of oven drying (Association of Official Analytical Chemists (AOAC), 2012).

**Moisture content**

Moisture content (dry basis) of banana slices for the experimented samples was calculated according to equation (1) (Corzo et al., 2008)

\[
MC = \frac{W_i M_{Ci} - (W_i - W_{i+\Delta t})}{W_i(1 - M_{Ci})}
\]

where \(W_i\) is the initial weight, \(W_t\) and \(W_{t+\Delta t}\) are the weight at drying time \(t\) and \(t + \Delta t\), respectively, and \(M_{Ci}\) is the initial moisture content.

**Drying rate**

The mass transfer rate that is defined as DR (dry basis) could be calculated by dividing the difference in product weight (\(\Delta W\)) within the period of time by \(\Delta t\) and dry solid weight (\(W_d\)) as following (Corzo et al., 2008)

<table>
<thead>
<tr>
<th>Instrument</th>
<th>Model</th>
<th>Accuracy</th>
<th>Make</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital balance</td>
<td>GF3000</td>
<td>±0.02</td>
<td>A&amp;D, Japan</td>
</tr>
<tr>
<td>T-sensor</td>
<td>LM35</td>
<td>±1°C</td>
<td>NSC, USA</td>
</tr>
<tr>
<td>RH-sensor</td>
<td>SHT15</td>
<td>±2%</td>
<td>China</td>
</tr>
<tr>
<td>V-sensor</td>
<td>405-V1</td>
<td>±3%</td>
<td>TESTO, UK</td>
</tr>
</tbody>
</table>

**Table 1. Specifications of instruments including their rated accuracy**

![Scheme of pilot plan thin-layer drying equipment.](image)
where $\varphi$ shows relative humidity of air, $P$ and $P_{vs}$ are atmospheric pressure and saturated pressure, respectively.

### Exergy efficiency

The exergy efficiency ($\eta_{\text{exergy}}$) is acquired using the following equation by dividing the exergy use (investment) in drying the product to exergy of the drying air provided to the system (Akpinar et al., 2006)

$$
\eta_{\text{exergy}} = \frac{\text{Exergy inflow} - \text{Exergy loss}}{\text{Exergy inflow}}
$$

$$
= 1 - \frac{\text{Exergy loss}}{\text{Exergy inflow}}
$$

(8)

Summation of inlet and outlet air exergy for fresh and dried product is obtained using the second law of thermodynamics. The following form of enforceable exergy equation was used for stable flow systems to reach this object (Ghasemkhani et al., 2016; Midilli and Kucuk, 2003)

$$
\text{Exergy} = m_{da}c_{pda} \left[ (T - T_{\text{ref}}) - T_{\text{ref}} \ln \frac{T}{T_{\text{ref}}} \right]
$$

(9)

where $m_{da}$ is the mass flow rate, $T$ is the inlet or outlet, and $T_{\text{ref}}$ is the reference temperature. The inflow and outflow of exergy, depended on the inlet or outlet temperatures of the drying chamber, were calculated using equation (9).

Exergy loss is determined by the following equation (Akpinar et al., 2006)

$$
\text{Exergy loss} = \text{Exergy inflow} - \text{Exergy outflow}
$$

(10)

In current research the reference temperature was taken as the environment: $T_{\text{ref}} = 28^\circ C$.

### Response surface methodology modeling

Experimental design and process optimization are two intertwined works. RSM mathematically expresses the relationship between the independent variables, air temperature, air flow velocity, and drying time, in polynomial model, which provided the responses as a function of relevant variables. A central composite design was employed for the present study to obtain the experimental data, which would fit full second-order polynomial models representing the response surfaces over a relatively broad range of parameters.
The principle of RSM was described by Castillo (2007). In the following function an experimental second-order polynomial model is shown for three elements

\[ y_k = a_0 + \sum_{i=1}^{3} a_i x_i + \sum_{i=1}^{3} \sum_{j=1}^{3} a_{ij} x_i x_j \]  

(11)

where \( y_k \) (\( k = 1, 2, 3 \) and 4) denote the predicted responses (moisture content, DR, energy efficiency and exergy efficiency) used as dependent variables; \( x_i \) (\( i = 1, 2 \) and 3) are the input predictors or independent variables (drying air temperature, air velocity and drying time); and \( a_0, a_i \) (\( i = 1, 2, 3 \)), and \( a_{ij} \) (\( i = 1, 2, 3; j = i, \ldots, 3 \)) were the model coefficient parameters. The least-squares method is used to determine the coefficient parameters through multiple linear regression analysis.

In the central composite design, all the elements were investigated at three various levels \((-1, 0, +1)\), two star points, and three repetitions at the center point (Myers and Montgomery, 2002).

The independent variables were taken at a central coded value assumed as zero. The minimum and maximum ranges of independent variables were considered. Table 2 presents the full experimental plan with respect to their values in actual and coded form. Upon completion of experiments, the values of moisture content, DR, energy efficiency, and exergy efficiency were taken to their values in actual and coded form. Upon completion of experiments, the values of moisture content, DR, energy efficiency, and exergy efficiency responses (outputs) were taken as dependent variables or responses \( (y_i) \). Four second-order polynomial equations were then fitted as the dependent variables or responses \( (y_i) \). Four second-order polynomial equations were then fitted by least-squares optimization method. These response surface models were also employed to predict the result by isoresponse contour plots. The projection of the response surface as a two dimensional plane was presented by contour plot (Karimi et al., 2012).

### ANN modeling

In the current study, experimental data were modeled using ANN, trained and simulated in Matlab software, with the Neural Network Toolbox (The MathWorks Inc., Natick, USA). Multiple input and multiple output network models were developed for the drying air temperature, air velocity, and drying time parameters (inputs) and for the moisture content, DR, energy efficiency, and exergy efficiency responses (outputs). The training of the network was supervised by standard Bayesian regularization back propagation training algorithm.

Minimization of error was accomplished using the Levenberg–Marquardt (LM) algorithm. It is one of the best methods to amend generalization performance of network for function approximation problems. Since it does not need that a validation data set be separated out of the training data set. This advantage is especially noticeable when the size of data set is small. It minimizes a linear combination of squared errors and weights and then defines the correct combination to generate network that distributes truly (Anderson, 1995).

During training, weighting functions for the inputs to neural network were determined, such that the predicted outputs best matched the actual output from the data set. Weights were randomly assigned at the beginning of the training phase, according to the backpropagation algorithm.

As depicted in Figure 2, the network architecture consisted of an input layer with three neurons, an output layer with four neurons, and a hidden layer, that the transfer function in the first layer is tan-sigmoid, and the output layer transfer function is linear.

The number of neurons in the input and output layers are given by the number of input and output variables in the process under investigation. In this study, the input layer consists of three variables in the process (air temperature, air velocity and drying time), and the output layer contains four variables (moisture content, DR, energy efficiency and exergy efficiency) for banana slices drying process. The optimal number of neurons in the hidden layer is difficult to specify, and depends on the type and complexity of the task, usually determined by trial and error.

To determine the optimal network configuration, the number of neurons in the hidden layer was determined by developing several networks that vary only with the size of hidden layer and simultaneously observing the change in the mean squared errors (MSEs). The optimum configuration was decided based on minimizing the difference between neural network prediction and desired output less than \( 10^{-4} \).

### Optimization

While there has been continuous interest in academic circles to apply different multi-objective optimization methods
techniques to solve optimization problems, few of them have involved the attention of applied or industrial statisticians (Castillo, 2007). In this study, desirability method was applied as one of the most famous approaches to optimization. The desirability function approach is one of the most widely used methods in industry for multiple response process optimizations. Its idea is according to concept that the “quality” of a product or process that has multiple quality characteristics, with one of them out of some “desired” limits, is wholly unacceptable. The technique finds operating conditions \( x_i \) that provides the “most desirable” response values (Karimi et al., 2012).

For each response \( y_k \), numbers between 0 and 1 were assigned as a desirability function \( d_k(y_k) \) according to the possible values of \( y_k \); that \( d_k(y_k) = 0 \) showing a completely undesirable value of \( y_k \) and \( d_k(y_k) = 1 \) representing a completely desirable or ideal response value. The individual desirabilities were then combined using the geometric mean, which provides the overall desirability (\( D \))

\[
D = (d_1(y_1) \times d_2(y_2) \times \ldots \times d_m(y_m))^{1/m} \tag{12}
\]

where, the number of responses is shown by \( m \). It is noticeable that if any response \( k \) is completely undesirable \( d_k(y_k) = 0 \) thus the overall desirability will be zero.

In practice, fitted response models \( y_i \) were applied in the method.

Different desirability functions \( d_k(y_k) \) can be used, contingent to whether a particular response \( y_k \) is to be maximized, minimized, or assigned to a target value. Derringer and Suich suggested an effective class of desirability functions (1980). \( L_k, U_k, \) and \( T_k \) were the lower, upper, and target values desired for response \( k \), respectively, where \( L_k \leq T_k \leq U_k \). If a maximum value results a complete desirability, the individual desirability is defined as

\[
d_k(y_k) = \begin{cases} 0 & \text{if } y_k(x_i) < L_k \\ \left( \frac{y_k(x_i) - L_k}{T_k - L_k} \right)^s & \text{if } L_k \leq y_k(x_i) \leq T_k \\ 1 & \text{if } y_k(x_i) > T_k \end{cases} \tag{13}
\]

where \( T_k \) is interpreted as a large enough value for the response and the exponent \( s \) define how strictly the target value is desired. For \( s = 1 \), the desirability function increases linearly towards \( T_k \), for \( s < 1 \), the function is convex, and for \( s > 1 \), the function is concave. In this study the value of \( s \) was equal to 1.

If a minimum value results a complete desirability, instead, the individual desirability is instead defined as

\[
d_k(y_k) = \begin{cases} 1 & \text{if } y_k(x_i) < T_k \\ \left( \frac{y_k(x_i) - L_k}{T_k - U_k} \right)^s & \text{if } T_k \leq y_k(x_i) \leq U_k \\ 0 & \text{if } y_k(x_i) > U_k \end{cases} \tag{14}
\]

where \( T_k \) denotes a small enough value for the response (Karimi et al., 2012).

![Figure 2. Schematic representation of multilayer artificial neural network used in the present study.](image)
RESULTS AND DISCUSSION

Interpretation of response surface methodology models

Current research, the effects of air temperature, air flow velocity, and drying time on moisture content, DR, energy efficiency, and exergy efficiency of banana slices drying were studied in a forced conductive dryer. The acquired results from the experimental data and corresponding points on fitted models by RSM have been displayed in Table 3. The importance of regression models was observable from the estimated Fisher’s ‘F’ values of 93.87, 56.87, 42.21, and 380.11 for responses of moisture content, DR, energy efficiency, and exergy efficiency, in order and a possibility (P) value of 0.000 for all responses. The large Fisher’s ‘F’ value shows that using the regression equation can predict most of the changes in the response. Moreover, p value used to diagnose if F is large enough to indicate statistical significance. The model is statistically significant if p value is lower than 0.05.

The regression consequences which were acquired from central composite design models are represented in Table 4, where p values are displayed along with the coefficients. The p value is considered as the minimum level of significance which is used to reject null hypothesis. Normally, a minor value of p consequences a more significant for the corresponding coefficient term (Karimi et al., 2012; Ravikumar et al., 2007).

Moisture content. The fitted moisture content model by means of RSM in terms of the experimental factors is as follows

\[
MC = 5.662 - 0.038 \times T - 1.399 \times V - 1.657 \times t \\
+ 0.011 \times T \times V + 0.005 \times T \times t \\
+ 0.121 \times V \times t + 0.152 \times t^2
\]  

(15)

where MC, T, V, and t represent moisture content, air temperature, air flow velocity, and drying time,

Table 3. Observed values of moisture content (MC), drying rate (DR), energy efficient (\(\eta_{\text{energy}}\)), and exergy efficiency (\(\eta_{\text{exergy}}\)) for drying banana slices based on central rotatable composite design and values of response surface methodology in design points

<table>
<thead>
<tr>
<th>Air temperature (°C)</th>
<th>Air velocity (m/s)</th>
<th>Drying time (h)</th>
<th>Experiment data</th>
<th>RSM model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MC (g_water/g_dsw)</td>
<td>DR (g_water/g_dsw.h)</td>
<td>(\eta_{\text{energy}})</td>
<td>(\eta_{\text{exergy}})</td>
</tr>
<tr>
<td>-1</td>
<td>-1</td>
<td>-1</td>
<td>1.26</td>
<td>1.00</td>
</tr>
<tr>
<td>-1</td>
<td>-1</td>
<td>1</td>
<td>0.38</td>
<td>0.69</td>
</tr>
<tr>
<td>-1</td>
<td>1</td>
<td>-1</td>
<td>0.75</td>
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</tr>
<tr>
<td>-1</td>
<td>1</td>
<td>1</td>
<td>0.10</td>
<td>0.72</td>
</tr>
<tr>
<td>1</td>
<td>-1</td>
<td>-1</td>
<td>0.79</td>
<td>1.48</td>
</tr>
<tr>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>0.11</td>
<td>0.86</td>
</tr>
<tr>
<td>1</td>
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<td>-1</td>
<td>0.48</td>
<td>1.43</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.06</td>
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</tr>
<tr>
<td>-1</td>
<td>0</td>
<td>0</td>
<td>0.46</td>
<td>0.87</td>
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<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0.20</td>
<td>0.91</td>
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<td>0</td>
<td>-1</td>
<td>0</td>
<td>0.55</td>
<td>0.91</td>
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<td>1</td>
<td>0</td>
<td>0.10</td>
<td>0.98</td>
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<tr>
<td>0</td>
<td>0</td>
<td>-1</td>
<td>0.77</td>
<td>1.28</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.13</td>
<td>0.76</td>
</tr>
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<td>0</td>
<td>0</td>
<td>-2</td>
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<td>1.76</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0.12</td>
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</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.32</td>
<td>0.97</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.31</td>
<td>0.95</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.31</td>
<td>0.94</td>
</tr>
</tbody>
</table>
respectively. The predicted values of the moisture content of banana slices obtained through equation (15) are close to the observed values acceptably.

The influence of the linear factors, the air temperature, air velocity, and drying time, on the moisture content of banana slices was very significant ($p = 0.0001$ for all the linear factors) in the hot air drying process. It was detected that square term of the drying time was significant ($p = 0.0001$). Because the squared term was significant which defined there was a curved line relationship between the moisture content and the square factor. Moreover, the interaction terms of the air temperature × the air velocity, the air temperature × the drying time and air velocity × drying time were detected to be significant in the model ($p = 0.028, 0.0.33$ and 0.016, in order). However, the squared terms, the air temperature and the air velocity ($p = 0.626$ and 0.696), were not detected to be significant.

A positive sign of the coefficient is indicative of a synergistic influence, but a negative sign displays an antagonistic effect. In this study, the influence of whole linear variables on the moisture content was negative. Consequently, if these factors increase, moisture content of banana slices will reduce. A positive relationship between the square terms and interaction terms significant in the model and the moisture content represents that by increasing these factors, the moisture content will increase too. In addition, according to the high values of $R^2$ (98.83%) and $R^2$ (adjusted) (98.09%) and low value of RMSE (0.060) there are a high dependence and correlation between the predicted and the experimental values of the moisture content. Hence this model can describe 98.09% of result of the whole variation.

**Drying rate.** A quadratic response surface model for the DR was found from multiregression analysis which is shown in the following equation

$$DR = -0.406 + 0.035 \times T + 0.664 \times V - 0.163 \times t - 0.009 \times T \times V - 0.006 \times T \times t + 0.062 \times t^2$$

where $DR$ is the drying rate. The influence of the linear elements: the air temperature and drying time, the square term drying time and also the interaction terms: the air temperature × the drying time and air temperature × air velocity were detected to be significant on the DR of banana slices in the hot air drying.

In order to avoid numerical instabilities as much as possible it must check the model hierarchy. For example, if the interaction ($T \times V$) is selected for DR model without selecting the main effect “parent” of the interaction, such as $V$, the resulting model would not be hierarchical. A well-formulated model must include all main effects present in the interactions (Karimi et al., 2012). The purpose of model as fitted for DR will be hierarchical; it includes the main effect of air velocity.
There was a negative relationship between the linear variable the drying time and the interaction terms significant in the model and the DR. The positive influence of the linear terms: the air temperature and the velocity and the square term drying time on the DR displays that by increasing these factors the DR will increase.

Energy efficiency. Multiregression analysis was done to obtain a quadratic response surface model for the energy efficiency which is presented in following

\[
e - \text{energy} = 4.118 - 0.076 \times T - 0.414 \\
	\times V - 0.127 \times t + 0.001 \times T^2 \\
+ 0.004 \times T \times V + 0.014 \times t^2
\]

where e-energy shows the energy efficiency. For energy efficiency of the utilized air drying in this study, the influence of all the linear elements, the square terms air temperature and drying time, and the interaction term temperature \(V\) velocity were detected to be significant although the influence of other terms were not significant. Influence of all the linear factors: air temperature, air velocity, and drying time on energy efficiency were negative. However two of the square terms, air temperature and drying time and the interaction term temperature \(T\) velocity had a positive influence on energy efficiency.

Exergy efficiency. The exergy efficiency fitted model using the RSM in terms of the experimental factors is equal to

\[
e - \text{exergy} = -0.532 + 0.042 \times T + 0.074 \\
	\times V - 0.008 \times t - 0.001 \times T^2 \\
- 0.023 \times V^2 - 0.009 \times t^2
\]

where e-exergy represents exergy efficiency. Apart from all the interaction terms, the influences of other factors and terms on exergy efficiency were considerable. All the terms significant in the model else of the linear term air velocity had a negative relationship with the exergy efficiency.

Contour plots of response surface models

A contour plot is a graphical technique to display a three-dimensional surface by plotting constant z-slices, named contours, on a two-dimensional format, which can be used to assess the individual and cumulative influence of the variable and the mutual interaction between the variable and the dependent variable (Ravikumar et al., 2007).

The isoresponse contour plots are shown in Figure 3, where moisture content of banana slices was represented by simultaneously varying two factors into their amplitude in coded units with a factor held as a constant at a coded value equal to zero. Whereas the air velocity had the least effect on responses in comparison of other factors, the combined effects of the two factors the air temperature and the drying time on the responses with the air velocity held as a constant are described in following then the other contour plots will be intelligible. In Figure 3(b), the lines of contour plots predict the values of moisture content for different temperature at different time. These values are more or less same to the experimental values. Moisture content obtained a minimum value equal to 0.2 g/g in high temperature and time and obtained a maximum value equal to 1.6 in low temperature and time simultaneously. The surface plot also describing individual and cumulative effect of these two test variable and test their subsequent effect on the response.

The contour plot of DR with velocity held as a constant at a coded value equal to zero is displayed in Figure 4(b). As seen in the figure, the DR was high at low drying time and while the drying time was increasing, the drying rate was decreasing. In other words, the high impact of time on the on DR has caused the temperature increase not to affect the DR, whereas in high drying time air temperature played no role on DR effectively. In the other word the strong effect of the time on DR was caused that increasing the temperature can’t be affected on the DR. It also can be found from the contour that maximum value of DR was obtained during maximum air temperature and minimum drying time, simultaneously by increasing the time, DR decreased gradually. This process of reducing the DR was more severe due to the increase in time at a lower temperature.

Figure 5 shows the contour plots of energy efficiency. The air temperature and the drying time in the plot (b) in the figure were varied into their amplitude and the air velocity was held on coded value equal to zero. As is found in the surface plot by increasing the temperature the energy efficiency was decreased so that maximum value for energy efficiency was obtained at the lowest temperature. However variations in drying time also affected the values of the energy efficiency, so that an increase in drying time caused a decrease in energy efficiency.

In contour plot (b) presented in Figure 6, it is found that by increasing the drying time, the exergy efficiency decreased; however varying temperature did not affect the values of the exergy efficiency.
Figure 3. Contour plots for predicted response surface of moisture content (MC); (a) when drying time is equal to zero, (b) at air velocity equal to zero, and (c) at air temperature equal to zero.

Figure 4. Contour plots for predicted response surface of drying rate (DR); (a) when drying time is equal to zero, (b) at air velocity equal to zero, and (c) at air temperature equal to zero.
Figure 5. Contour plots for predicted response surface of energy efficiency ($\eta_{\text{energy}}$); (a) when drying time is equal to zero, (b) at air velocity equal to zero, and (c) at air temperature equal to zero.

Figure 6. Contour plots for predicted response surface of exergy efficiency ($\eta_{\text{exergy}}$); (a) when drying time is equal to zero, (b) at air velocity equal to zero, and (c) at air temperature equal to zero.
Interpretation of ANNs

A self-organizing feature map network based on “trainbr” was applied to predict the processes of the hot air drying for banana slices. To train the network in the computer, a set of factors was applied. In order to determine the optimal network topology, several repetitions were carried out with various numbers of neurons of hidden layer. At first it has two neurons then the number of neurons was increased up to 17. The minimum MSE value and a good prediction of the outputs of both training and test sets were acquired with 15 neurons in the hidden layer (Figure 7). Table 5 displays the moisture content, DR, energy efficiency, and exergy efficiency values for using trained ANNs in design points. As shown in the table, the low values of %error for the network outputs corresponding design points demonstrated that there was a good agreement between the network outputs and corresponding data related to the experimental samples. In Figure 8 also it is detected that high values of $R^2$ and an adequate accordance in the linear regressions were related to the network outputs in the design points. The similar results were achieved for prediction of energy and exergy in microwave assisted thin-layer drying of pomegranate arils using ANNs (Nikbakht et al., 2014).

Optimization based on the learned ANN

One of the significant steps in the design and analysis of experimentation is discovering the levels of factors which optimize the response. Because of working with more than one response in this study such as moisture content, DR, energy efficiency, and exergy efficiency, simultaneous multiple response optimization was performed.

In current investigation that included multiple responses, the acceptability of the process relied on more than one response. In order to optimize the process, moisture content need to be as low as possible and DR, energy efficiency and exergy efficiency need to be as high as possible.

In such situations the desirability of the process relies on the simultaneous optimization of all responses. Using the desirability profile and its function the optimization was performed.

In the application, all the factors, the air temperature, air velocity and drying time, were set into the network’s input layer, but two factors were stable and only one factor was adaptable. Before starting optimization, an experiment data was applied as an initial data (0, 0, and 0 in coded units for the air temperature, air velocity, and drying time, respectively). The simulation represented while the air temperature, air velocity, and drying time values were equivalent to 0.42 (74.2°C), 1.00 (1.50 m/s), and –0.17 (2.50 h) in the coded units, respectively; the desirability had a maximum value of 0.61 in order to acquire moisture content of 0.14 g/g, DR 1.03 g water/g h, energy efficiency 0.61, and exergy efficiency 0.91. The banana slices optimum drying process is represented in Table 6 and Figure 9.

![Figure 7. Curve of MSE to training subset and test subset. MSE: mean squared error.](image-url)
Table 5. Obtained values of moisture content (MC), drying rate (DR), energy efficiency ($\eta_{\text{energy}}$), and exergy efficiency ($\eta_{\text{exergy}}$) for drying banana slices using artificial neural networks in design points.

<table>
<thead>
<tr>
<th>Air temperature (°C)</th>
<th>Air velocity (m s$^{-1}$)</th>
<th>Drying time (h)</th>
<th>ANN model</th>
<th>ANN error (%)</th>
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</table>

Figure 8. Linear regression between the network outputs and the corresponding targets: (a) the data is related to moisture content, (b) the data is related to drying rate, (c) the data is related to energy efficiency, and (d) the data is related to exergy efficiency.
A multiple input and multiple output network trained by back propagation algorithms was developed to predict the moisture content, DR, energy efficiency, and exergy efficiency based on the three input variables (air temperature, air velocity and DR). The surfaces were assessed at 19 experimental points. The purpose of the research was to fit models to predict surfaces using the RSM and the ANN and to optimize for acquiring the maximum admissibility using desirability functions methodology. The contour plots pertaining to fit functions by means of RSM explained the influences of the factors on values of each response individually and cumulatively. In conclusion, the trained ANN found the maximum desirability point to minimize the moisture content and to maximize the DR, energy, and exergy efficiency as 0.42 (74.2°C), 1.00 (1.50 m/s), and −0.17 (2.50 h) for the air temperature, air velocity, and DR, respectively, to acquire moisture content equal to 0.14 g/g, DR equal to 1.03 g water/g h, energy efficiency equal to 0.61, and exergy efficiency equal to 0.91. As a result taking into consideration the results from modeling analyses, it can be concluded that ANN and RSM models demonstrated reasonable performance in predicting dryer parameters regarded as moisture content, DR, energy efficiency, and exergy efficiency criteria.

### DECLARATION OF CONFLICTING INTERESTS

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

### FUNDING

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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### APPENDIX

### Notation

- $a_{ij}$: model coefficient parameters
- $A_{dc}$: surface area of cross section (m$^2$)
- $C_{pda}$: specific heat of dry air (kJ/kg K)
- $DR$: drying rate (g water/g h)
- $h_{def}$: specific enthalpy of dry air at initial (kJ/kg)
- $h_{det}$: specific enthalpy of dry air at t time (kJ/kg)
- $h_{fg}$: latent heat of vaporization (kJ/kg)
- $L_k$: lower value desired for response $k$
- $m$: number of responses
- $m_{da}$: mass flow rate of dry air (kg/s)
- $M_{Ci}$: initial moisture content (g/g)
- $P$: atmospheric pressure (kPa)
- $P_{rs}$: saturated pressure (kPa)
- $t$: drying time (h)
- $T$: temperature (°C or K)
- $T_k$: target value desired for response $k$
- $T_{ref}$: reference temperature
- $U_a$: air flow velocity (m/s)
- $U_k$: upper value desired for response $k$
- $V$: air flow velocity (m/s)
- $w$: humidity ratio of air (–)
- $W_d$: dry solid weight (g)
- $W_i$: initial weight (g)
- $W_t$: weight at drying time $t$ (g)
- $W_{t+\Delta t}$: weight at drying time $t + \Delta t$ (g)
- $x_i$: independent variables
- $y_k$: predicted responses
- $\Delta W$: difference in product weight (g)
- $\eta_{energy}$: energy efficiency
- $\eta_{exergy}$: exergy efficiency
- $\rho_a$: air density (kg/m$^3$)
- $\varphi$: relative humidity of air